HF Geolocation Phase 1a Overview

Scott Francis, Leidos

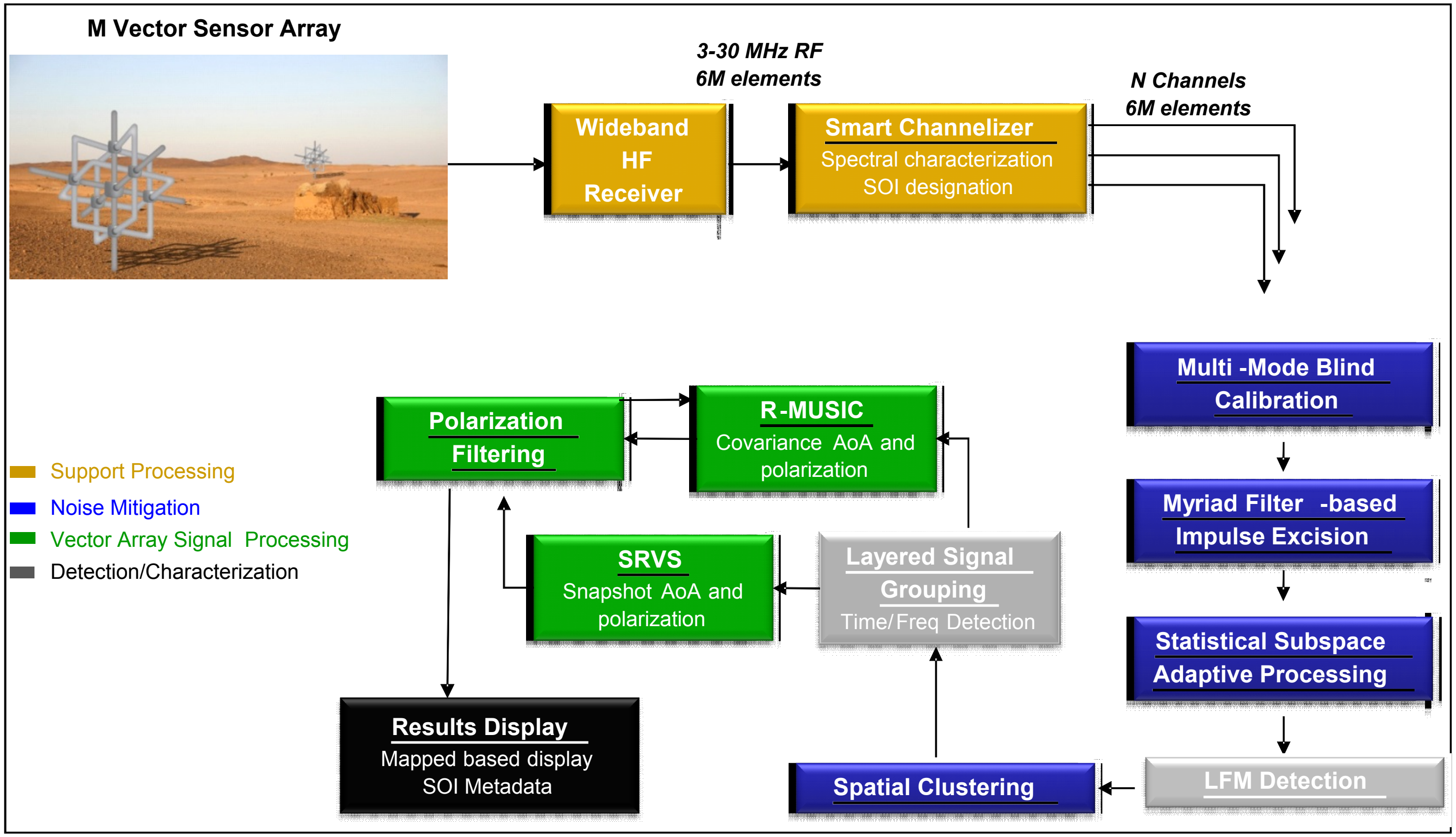
Outline

- Introduction
- Technical Approach
- Significant Findings and Results
- Conclusion

Introduction

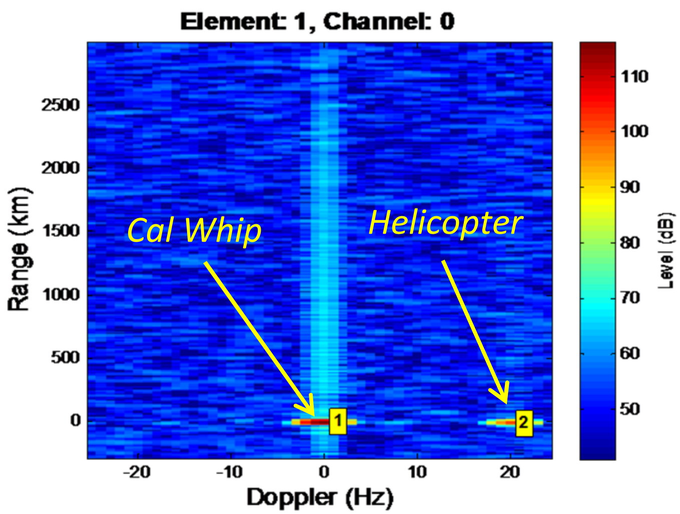
- The Leidos HF Geolocation (HFGeo) technical approach comprised an integrated algorithm suite for geolocating HF signals using vector sensors
- It addressed the four core technical areas of (1) noise mitigation, (2) vector array signal processing, (3) geolocation (later deemphasized), and (4) characterization
  - Detection is distributed over the channelization and signal processing functions
- Each of these algorithms was integrated into the Leidos HFGeo testbed, a configuration driven data analysis tool that successively applies detection, interference mitigation, and angle estimation followed by a display and archiving of results

Signal Processing Architecture

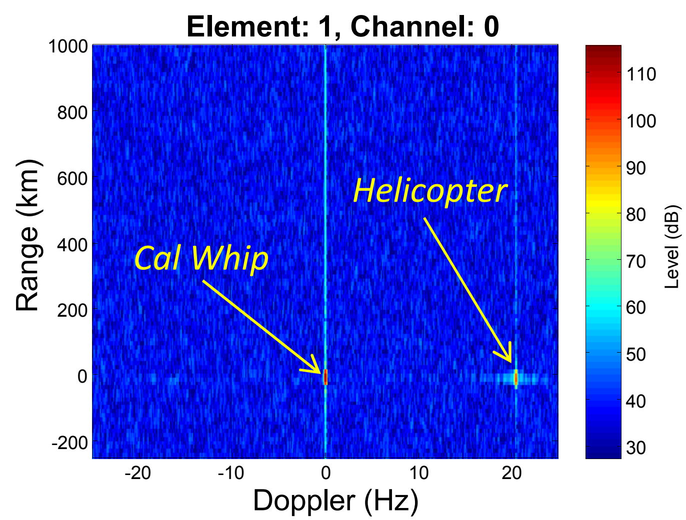


Calibration

- The primary calibration source provided for both Phase 0 and Phase 1A was a vertical whip antenna relatively close to the Vector Sensor Array
  - 195m in Phase 0 and 60m in Phase 1a
- Assumed a vertically polarized wave at an elevation of 0 degrees incident on the sensors
- Since the fields from the cal whip are almost certainly more complicated than assumed, especially for Phase 1a, the calibration weights obtained in this manner were meant to result in reasonable first-order approximations – to be refined with corrections from, for example, Robust MUSIC or the MMSC algorithm.

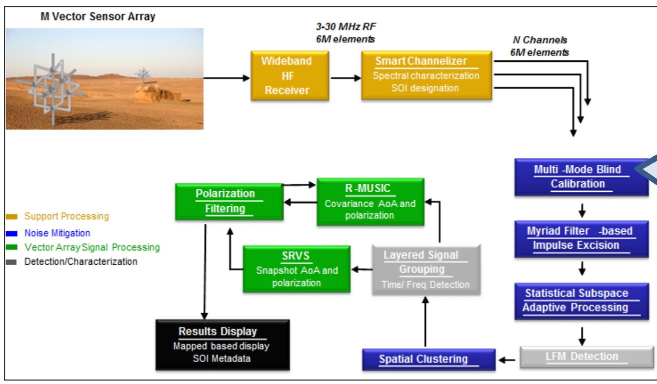


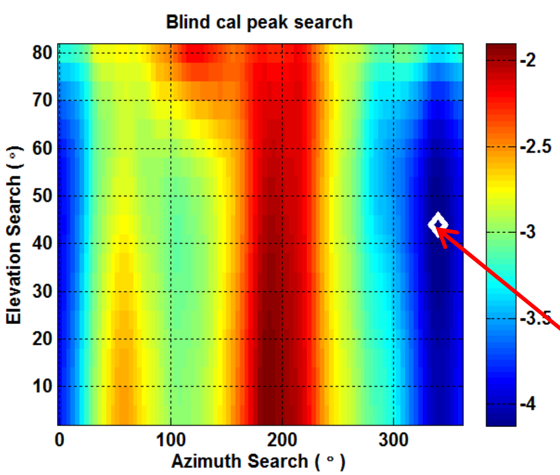
1 second CPI



20 second CPI

Multi-Mode Self Calibration (MMSC)





- MMSC is an approach for blind estimation of angle of arrival and calibration vectors
- STRAD developed a formulation to estimate calibration based on a Maximum Likelihood approach
- Estimator is used to compute minimum cost (or maximum likelihood) as a function of AOA
- Typically start with cal weights based on, e.g., cal whip data, although not necessary
- Two parameters required:
  - λ (ratio of the noise and calibration prior variances) – typically 0.5
  - Number of eigenvectors used – typically 4

Minimized cost function (PSK data from 8/13/13)

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Impulsive Noise Mitigation

- **Impulsive Region Detection**
  - Measure the linearity of small windows of received data and estimate the parameters of an α-stable distribution for the data
  - If the data is "peaky" or "heavy tailed" then it will have a higher proportion of impulsive samples

- **Subband Soft Limiting Impulse Mitigation**
  - Apply soft limiting to impulsive samples by applying a "Weighted Myriad Filter" to that region of data.
  - The Weighted Myriad Filter (WMyF) forms a non-linear estimate of location for each window of data that greatly reduces the influence of outliers
  - A "center-weighted" weight vector is used that allows center samples to be preserved unless they are true outliers
  - The result is similar to a median smoother, but more robust

Myriad Filtering Definitions:

K = Linearity Parameter

w = weight vector

$\{x_n\}$ = data samples

$$MYRIAD\left[K;\{x_n\}_{n=1}^{N}\right]=\hat{\theta}_k=\arg\min_{\theta}\prod_{i=1}^{N}\left[1+\left(\frac{x_i-\theta}{K}\right)^2\right]$$

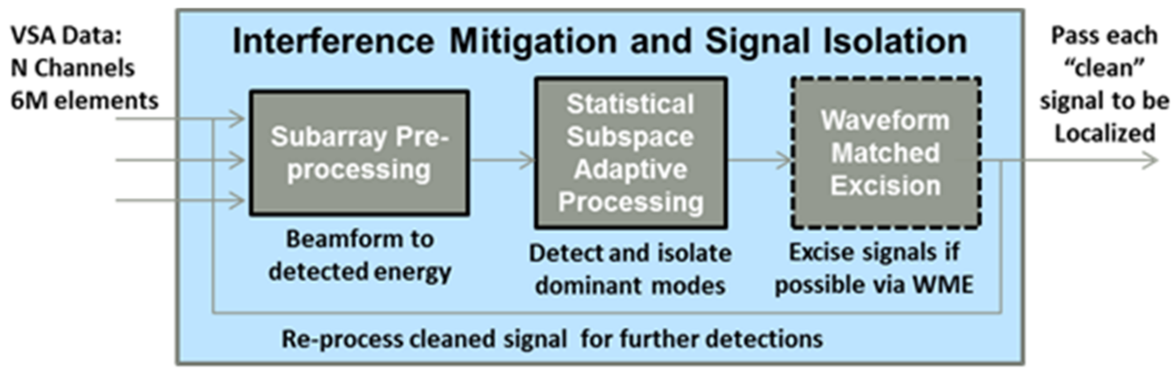
$$Wgtd.MYRIAD\left[K;\{x_n\}_{n=1}^{N}\right]=\hat{\theta}_k=\arg\min_{\theta}\prod_{i=1}^{N}\left[1+w_i\left(\frac{x_i-\theta}{K}\right)^2\right]$$

Interference Mitigation and Signal Separation

- The Leidos Team's HFGeo solution for noise mitigation centered around two major techniques—Statistical Subspace Adaptive Processing (SSAP) and Spatial Clustering.
- Both techniques took advantage of spatial and temporal degrees of freedom provided by the vector sensors to reject noise or interference and isolate signals of interest.

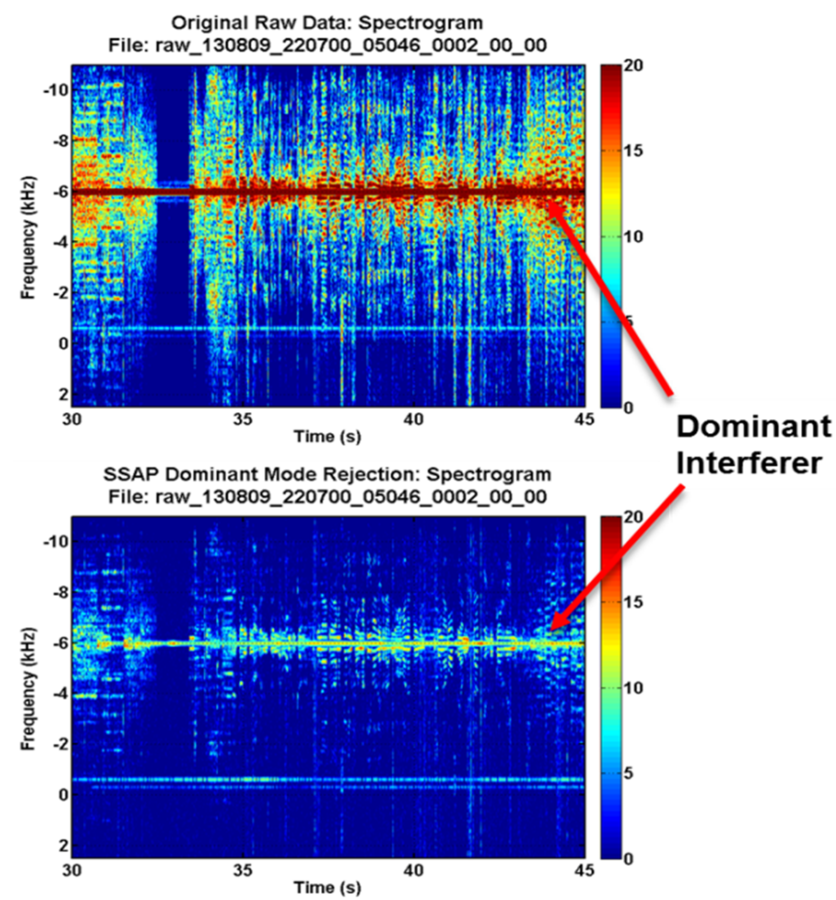
SSAP

- SSAP processing is the core of a suite of algorithms aimed at mitigating interfering signals to enable the detection and estimation of weaker signals
- Major techniques:
  - Dominant Mode Rejection
  - Waveform-Matched Excision



Dominant Mode Rejection

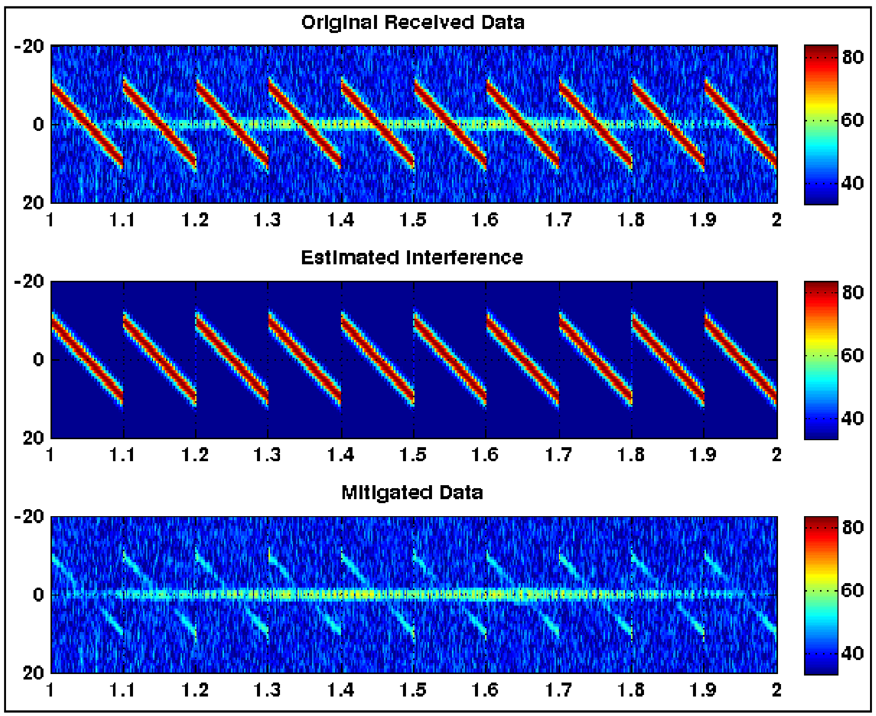
- Dominant Mode Rejection is tailored to automatically target the most dominant signal in the spectrum and isolate it in the time, frequency, and spatial domains
- This signal is then mitigated to enable further detection of weaker signals by beamforming away the dominate signal
- In the case that a signal does not have additional structure that can be used to improve the narrowness of the excision, a null is steered in the direction of the dominant signal



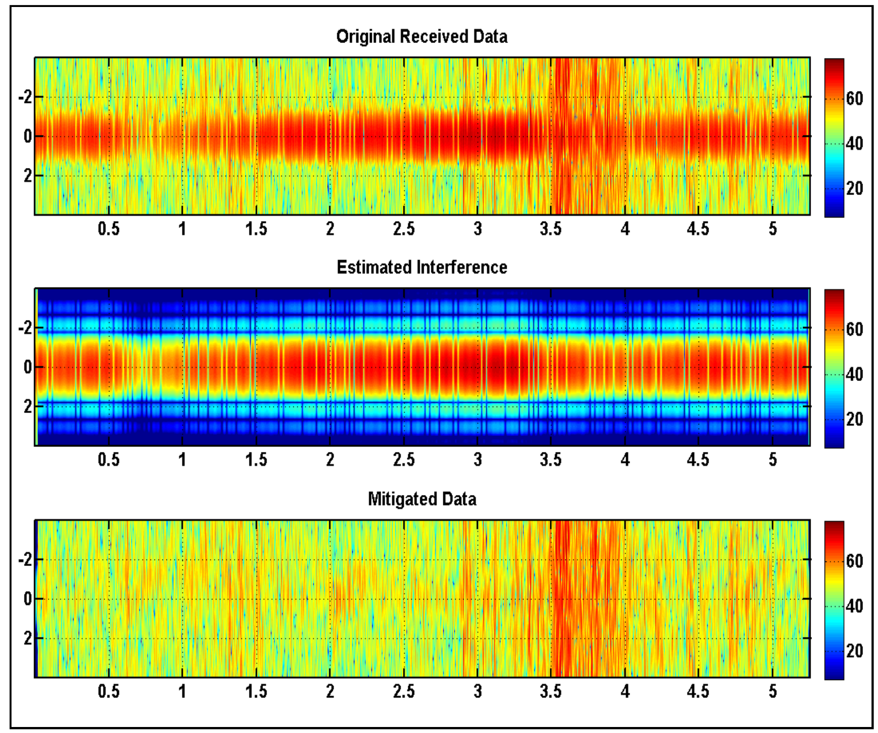
An example of DMR for the AM Radio Habana signal

Waveform Matched Excision

- In the cases where a signal is structured, such as an LFM or PSK31 signal, Waveform Matched Excision attempts a better fit of the interfering signal allowing much more precise excision



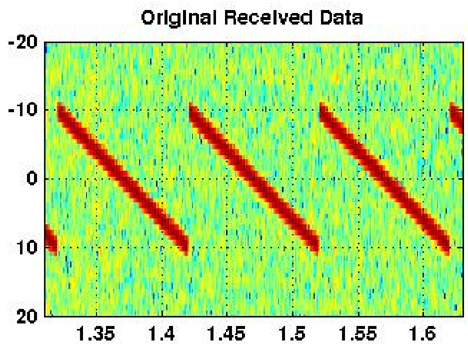
AM Signal Beneath an LFM interferer

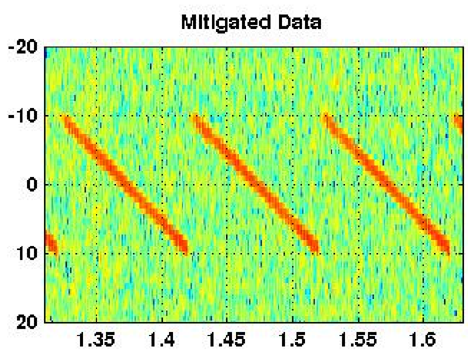


Excision of a PSK31 interferer

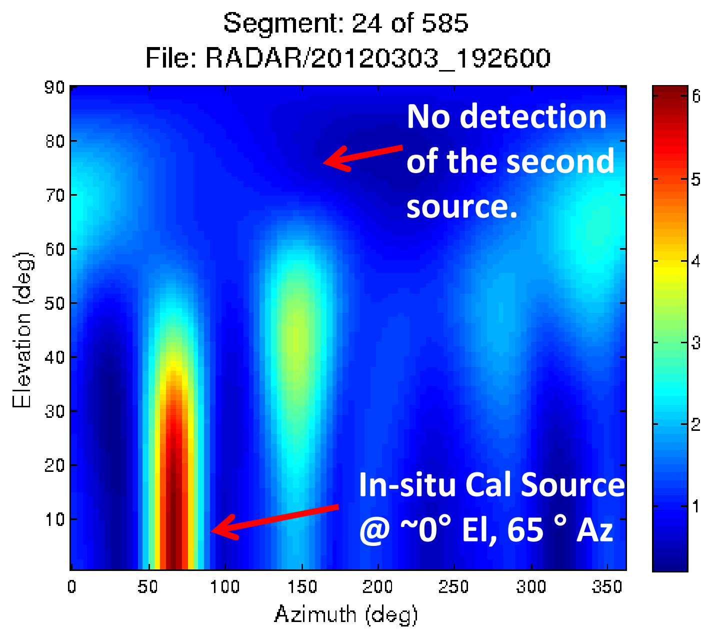
Example Radar Excision Result

Excising the Dominant In-situ Cal LFM Interferer

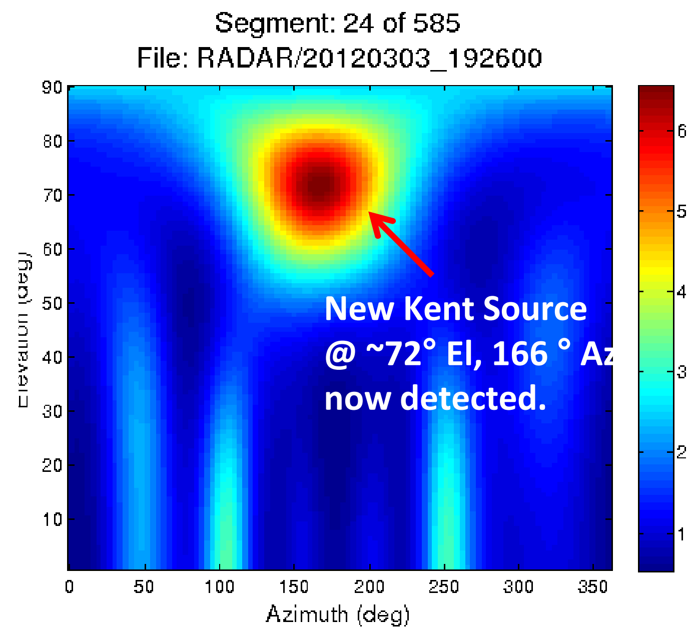




Raw MUSIC Result:



MUSIC after LFM Excision:



The In-situ cal source was ~13dB higher power and about 2ms earlier than the source at New Kent, but after excision the New Kent signal was accurately located.

Spatial Clustering

Time-Frequency Plane Based Spatial Clustering

- The time frequency distribution of received signals allow for spatial separation
  - Unique signals will have periods where each occupies independent portions of the time frequency (TF) plane
  - Using the TF plane for each element of a receive array allows estimation of a “clean” steering vector
  - These steering vectors can be used to initiate clustering
  - Use the “class” covariances to determine the angles of arrival or use spatial eigenvectors to separate the signals

Computing the Classes

Calculate:

spectrogram(*t*,*f*) = STFT(*t*,*f*) for each of the *N* elements

v(*t*,*f*) = “steering vector” from each array element’s STFT (1x*N*)

Classify:

Choose the “steering vector” with the highest STFT energy v_{max} and compute the “cosine similarity”

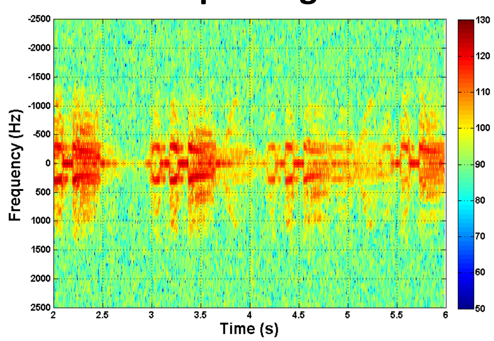
$$similarity = \frac{v_{\max} \cdot v(t,f)}{\|v_{\max}\| \|v(t,f)\|}$$

If the similarity exceeds a threshold, add that vector to the class.

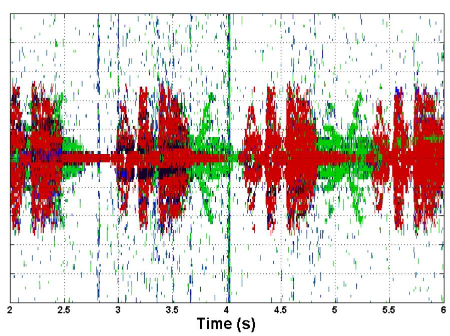
Example: Two AM Sources

Spatial clustering enables classification of the two interfering signals in the time and frequency plane.

Raw Spectrogram



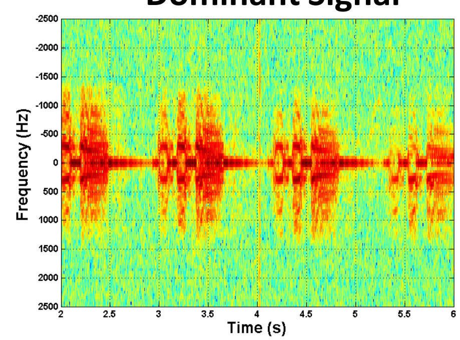
Clustering Result



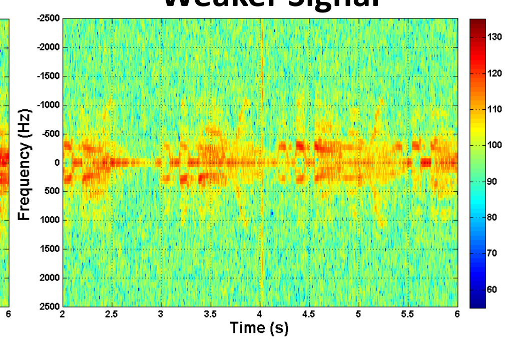
Separating Signals via Cluster Results

Using the spatial eigenvectors from each signal class, signals can be further isolated

Isolated Spectrogram of Dominant Signal



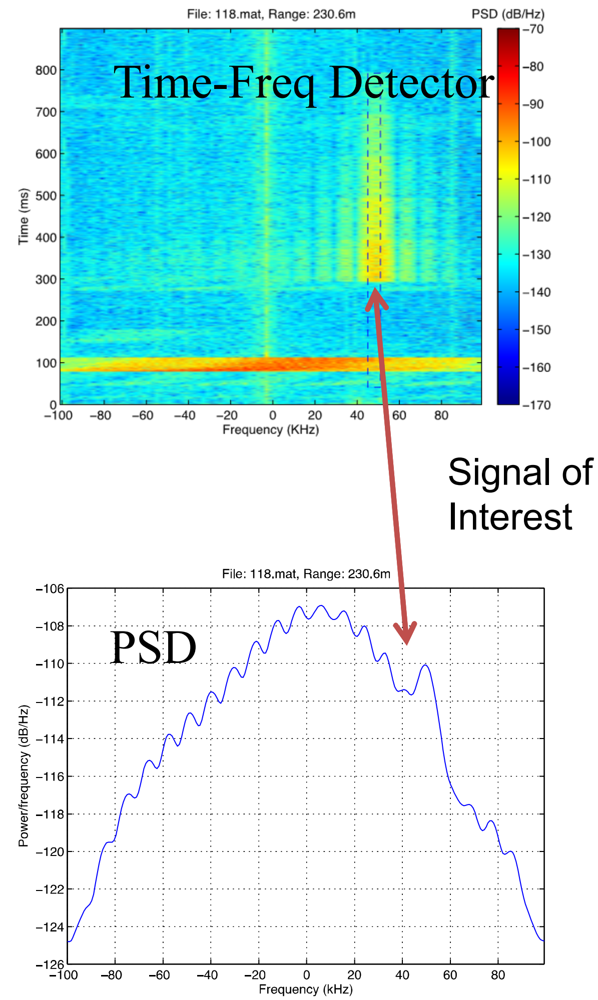
Isolated Spectrogram of Weaker Signal



Detection Algorithm: Layered Signal Grouping

- Work with a Leidos teammate (Dr. Berndt-Peter Paris of GMU) on another R&D program (DARPA's Radiomap), led to a spectrogram (rather than periodogram) based detector with superior detection performance.
  - By detecting in the time-frequency domain rather than just the frequency domain, one can both avoid "blocking" wideband signals and optimally constrain incoherent integration to the time the signal is truly on.
  - Identifies regions of spectrogram where energy is consistently higher than noise floor using GLRT algorithm
  - For each such identified signal "rectangle," provides center frequency, bandwidth, signal start, signal duration, and average power

- Value is pronounced in the presence of bursty interference.



Angle Estimation Algorithms: Vector Sensor Signal Processing

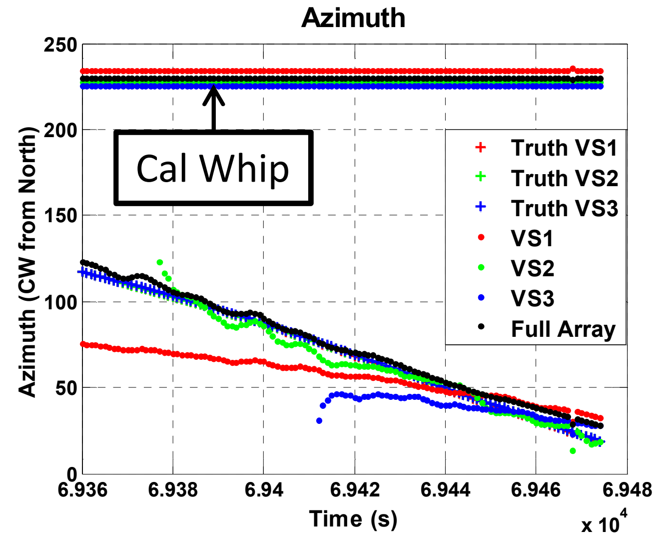
- MUSIC based algorithms
  - Standard MUSIC
    - With minor variants
  - Robust MUSIC
    - Computationally intensive, used primarily for optimizing calibration weights
      - Provides corrections to 1st order cal weights from, e.g., cal whip
    - Based on Robust Capon Beamforming, with following differences:
      - We want to minimize the projection into R_{noise} rather than R_{data}^{-1}
      - We must find the optimum polarization for the perturbed steering vector
  - G-MUSIC
    - Based on Random Matrix Theory
    - Estimation based on sample covariance matrices is enhanced by considering the expected distribution of eigenvalues around the values of the true covariance matrix, using the G-estimation method

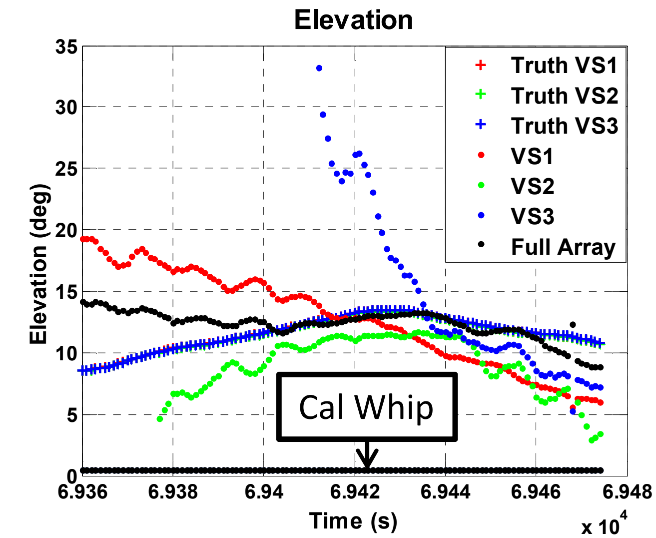
Angle Estimation Algorithms: Vector Sensor Signal Processing (cont)

- Sparse Reconstruction Techniques (L_1–norm)
  - Basis Pursuit DeNoise (BPDN)
    - Uses Spectrally Projected Gradient Method
    - Allows reasonably accurate angle estimates using small sample support (as small as single snapshot)
    - Still somewhat computationally intensive
  - Orthogonal Matching Pursuit (OMP)
    - OMP is a greedy, iterative algorithm based on successive projections of the data onto a highly redundant “dictionary” of possible signal constituents.
    - Less accurate than BPDN, but much more computationally efficient
- Sub-Array Processing
  - Above estimation techniques typically give detection at angle near true angles of unresolved O-, X-modes
  - Form sub-arrays from total Vector Sensor Array
    - Form broad null (in angle and polarization) and place on one principal circular polarization for each sub-array using MVDR beamformer.
    - Resulting array of beamformer outputs still has degrees of freedom that can be used to solve for angle and polarization of remaining, near orthogonal circular polarization

In Situ Whip Calibration

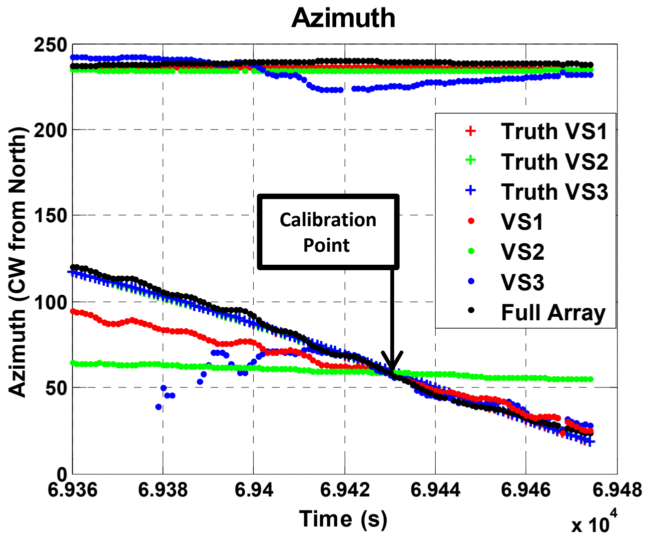
- To the right are plots of MUSIC angle estimations from the helicopter data from 8 Aug for each EMVS separately and for the full array.
- In Situ weights were generated from the data collected at 19:10:00, and the estimates/truth are from the 19:16:00 file on the same day.
- Significant variability is evident.
  - Is element-to-Rx channel mapping correct for all sensors?
  - Is sensor-to-sensor coupling a problem?
  - Are all of the sensor orientations correct?
  - Does the near field look significantly different from our assumptions?
- Using the single In Situ whip as a starting point for auto-focusing techniques may be challenging.

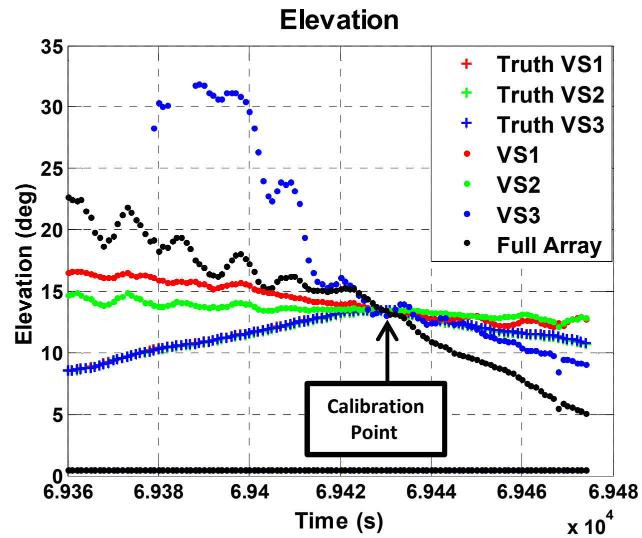




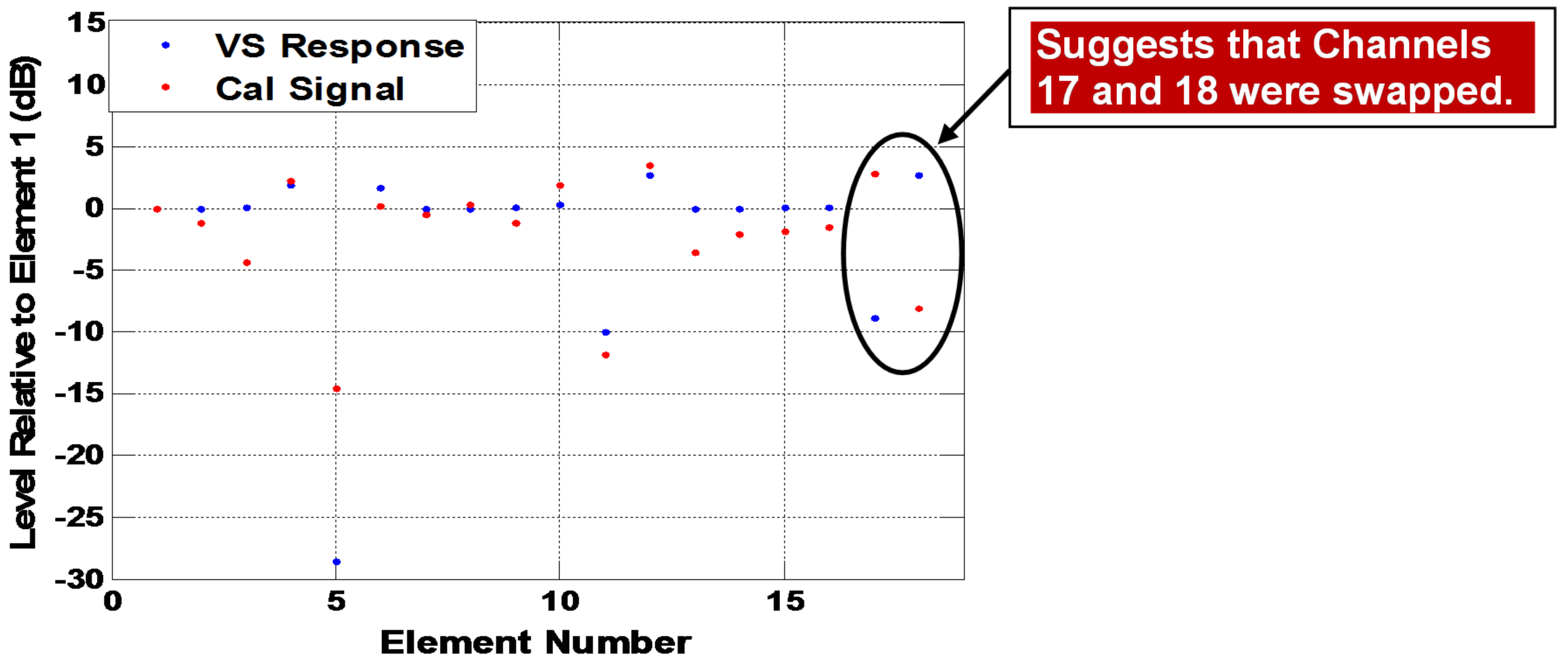
Helicopter Calibration

- As an alternate test of calibration quality, the 8 Aug helicopter data was used to generate calibration weights, instead of the In Situ whip
  - Same technique as for In Situ, but integrated over just 1 second of data, since the helicopter is moving
  - Helo cal signal is from 19:17:10 (70 seconds into file raw_130808_191600_9200_0020)
  - Helo angles at cal point: Az = 60 deg, El = 13.5 deg
- To the right are plots of MUSIC angle estimates from the helicopter data from 8 Aug for each EMVS separately and for the array.
  - All estimates diverge from truth as one moves away from the point where the cal signal was taken
  - The calibration may be adequate for the full array in azimuth
  - Elevation stability is markedly worse



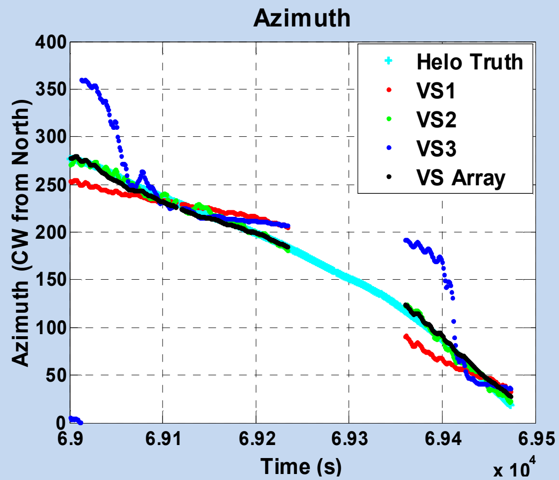


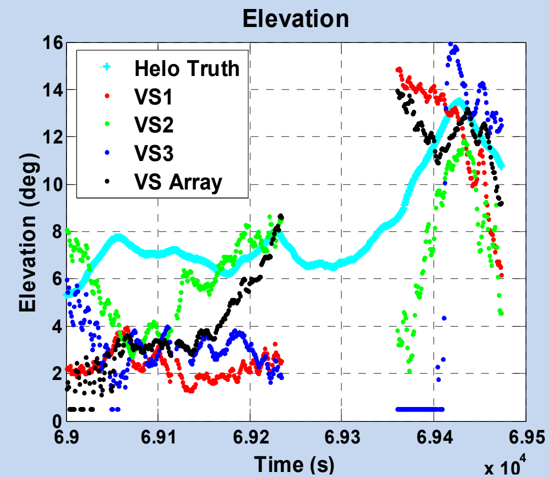
Calibration Challenges



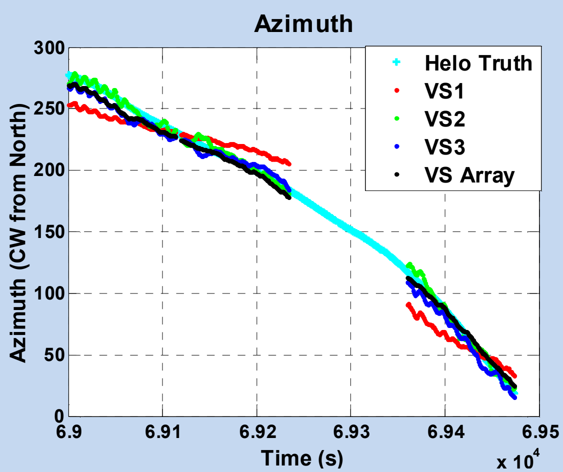
Swapping Channels 17 and 18

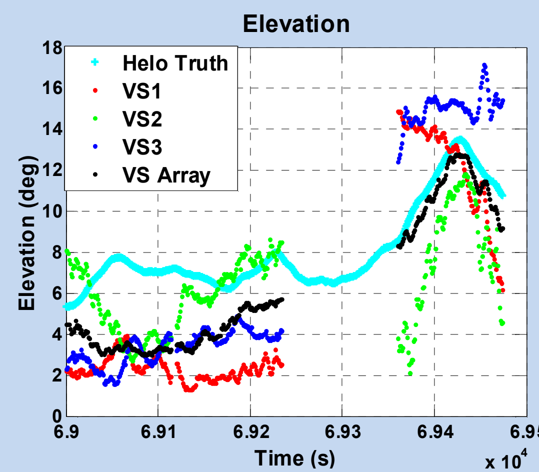
Before



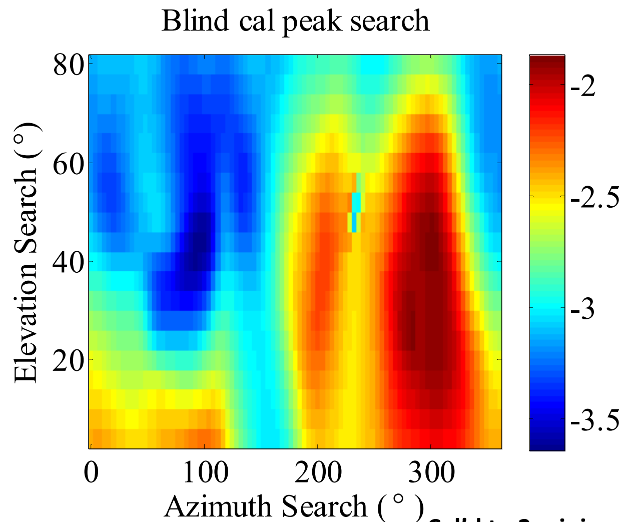


After



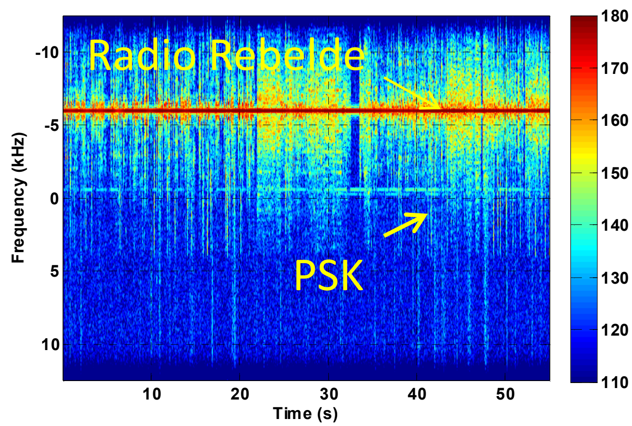


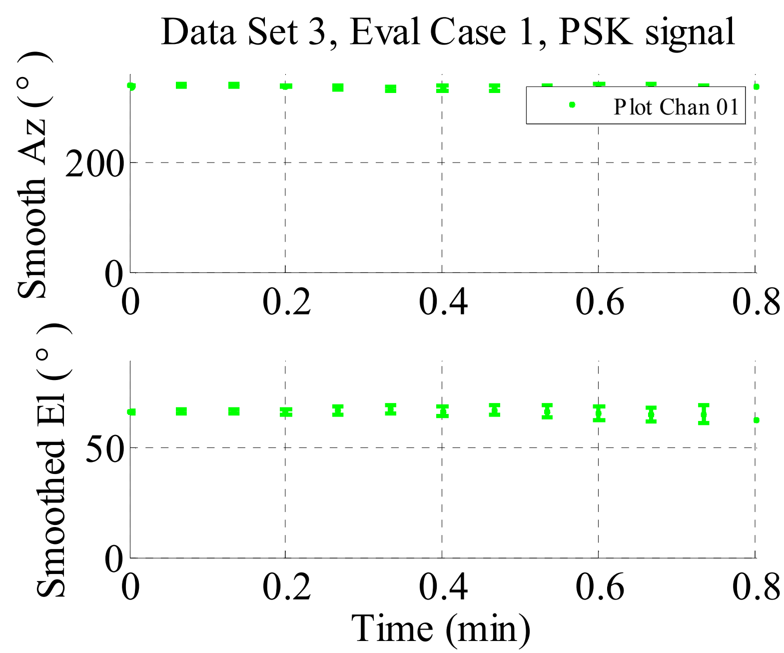
Angle Results: Case 1 (8/9 22:07-22:08)



Cal'd to 2 minima

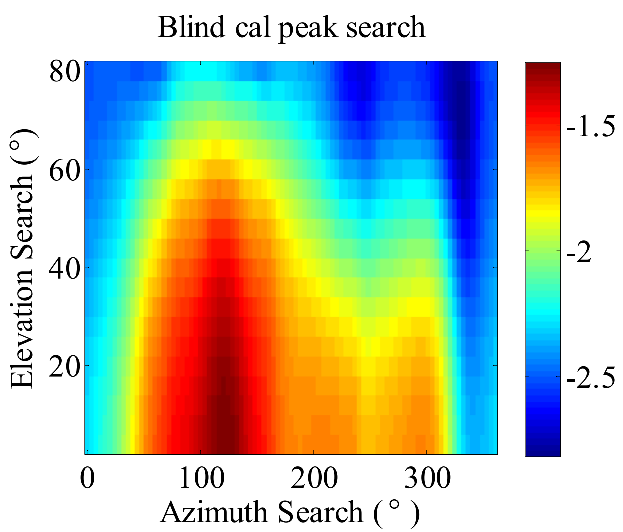
Signal: PSK, -603 Hz shift, filtered to 60 Hz.
4 sec CPI, 20 sec sliding window average
Plot chan 1: Music, SA unreliable
Azimuth σ = 5° μ = 335°
Elevation σ = 2° μ = 67°



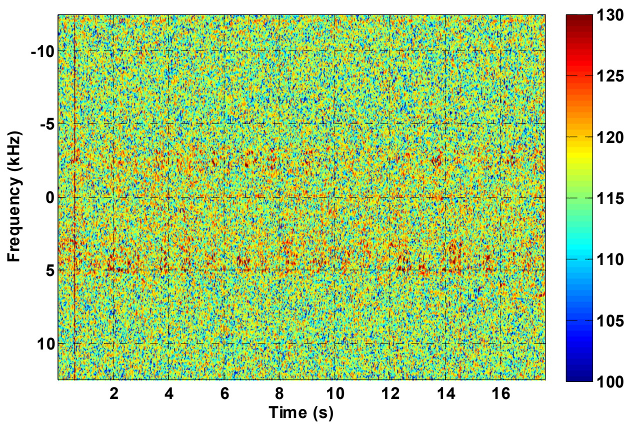


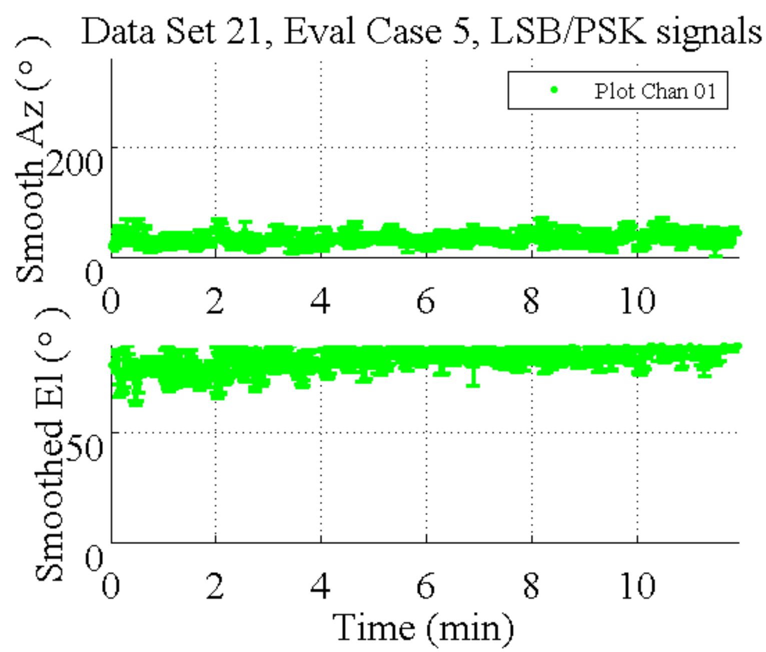
Should be NNW…

Angle Results: Case 5 (8/13 15:55-16:05)



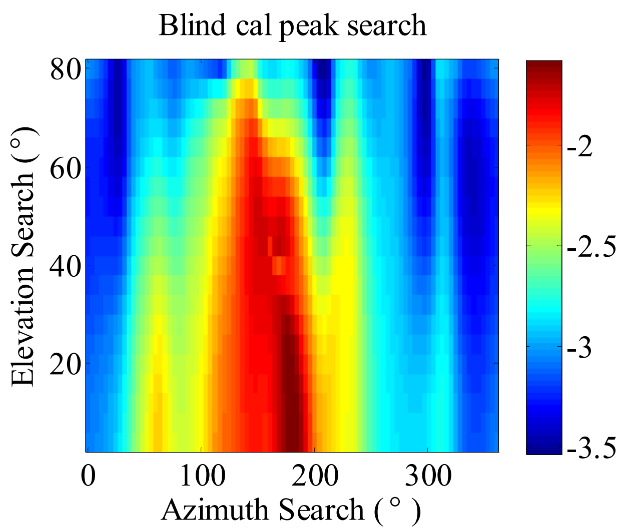
Signal: LSB, +3 kHz shift, filtered to 4 kHz.
1 sec CPI, 20 sec sliding window average
Plot chan 1: Music, SA excessively noisy
Az $\sigma = 9^o$ $\mu = 34^o$
El $\sigma = 3^o$ $\mu = 81^o$

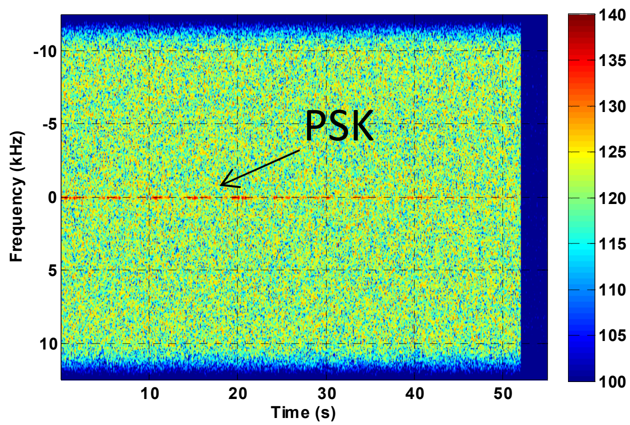




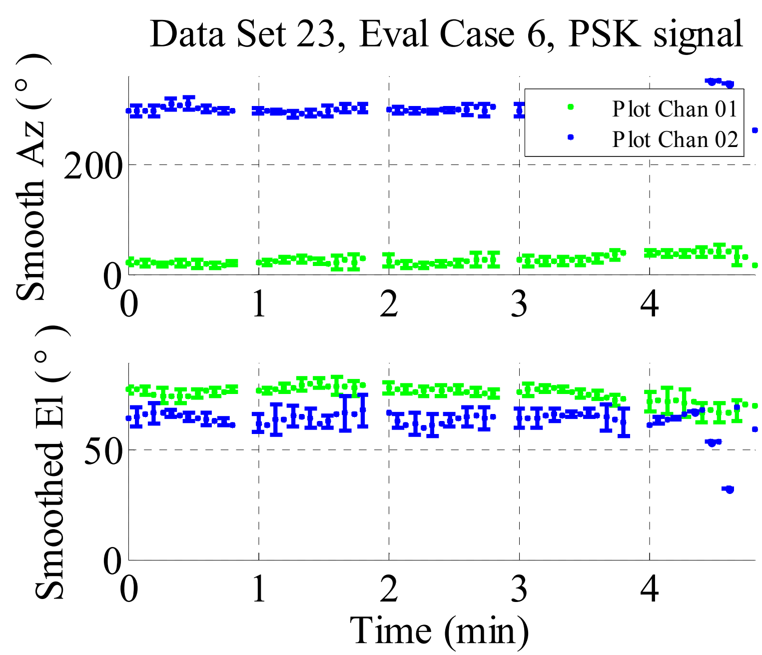
Should be NNE…

Angle Results: Case 6 (8/13 18:24-18:29)





Signal: PSK, 0 Hz shift, filtered to 60 Hz.
4 sec CPI, 20 sec sliding window average
Plot chan 1/2: Music, SA result unreliable
Az σ = 7^{o}, 7^{o} μ = 24^{o}, 299^{o}
El σ = 2^{o}, 4^{o} μ = 77^{o}, 65^{o}



Should be WNW…

Conclusion

- Significant progress was made on interference mitigation, signal characterization, and separation in the HF domain
- Direction finding performance was less than satisfying in many cases
  - Limited calibration data sources
  - Potential cable swap on data collect
  - Some equipment swapped out during data collects due to failures
- Good reason to believe that with better calibration data and array geometry that DF performance could have been better